Feasibility of Energy Detection for Dynamic Spectrum Access

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Abstract

In the *Adaptive Ad-hoc Free band Wireless communications* (AAF) project, a radio system is investigated that senses its environment to detect un-utilised radio spectrum and use it for ad-hoc networking. In this paper the performance in terms of Quality of Detection (QoD) of a simple energy detection system is studied. It is shown that noise-level uncertainty poses a hard limit on the detectability of signals. In the case that sub-noise signal detection is required, a noise-level measurement function may have to be included in the system architecture.

1 Introduction

In case of large scale (industrial) disasters, it was observed that current day emergency services lack capabilities (e.g. in offered data rates or video support) and are themselves not disaster proof as they are infrastructure-based (like TETRA or GSM). Some form of infrastructure-less wireless networking is needed and radio spectrum has to be available for it. What one could do is to claim radio resources for emergency purposes and design the disaster-relief network using these resources . . . However, the radio spectrum is fully allocated, although not always utilised (as was observed in e.g. [1, Appendix D]). Moreover, disasters like severe industrial explosions do not occur often enough to allocate huge amounts of scarce radio resources exclusively for the relief services.

The goal of the *Adaptive Ad-hoc Free band Wireless communications* (AAF) project [2] is to research and demonstrate a Cognitive Radio system, which continuously adapts its communications scheme to the available resources. Cognitive Radio is defined as a radio that can change its transmission based on interaction with its environment [1]. In the AAF project, a Bluetooth-based OFDM system [3] was suggested, using the reconfigurable platform in [4].

Two new approaches in radio frequency management are Dynamic Spectrum Access (DSA) in case policies are used, and Opportunistic Spectrum Access (OSA) in case when *only* scanning is used [5].

In DSA, access to new radio resources is purely dynamical and ad-hoc based. Specifically, radio access of a DSA system to a band for which it has no legal rights can be performed under the condition of causing no or minimal interference to the actual

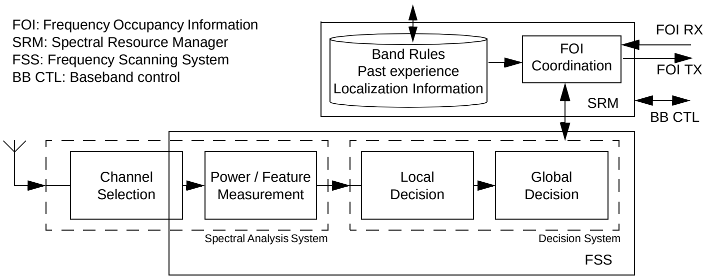


Figure 1: Spectrum Scanning System (SSS).

owner of that band (in this context called the Primary User (PU) or Licensed User (LU)). The interference level in a DSA network (DSAN) has to be such that it will not affect the perceived QoS parameters of the LU.

The radio system of a generic node consists of a baseband processing part (receiving and transmitting parts) and a Spectrum Scanning System (SSS). The latter, see figure 1, consists of Frequency Scanning System (FSS) and a Spectral Resource Manager (SRM). While the FSS is responsible for detection and digital signal processing, the SRM function is hosting the decision-making entity. Basically it is a MAC layer entity that controls both the baseband processing system and the FSS. It uses policies, localisation information and past-experience and decides where to scan and what usage is to be made of the scanning information. Each generic DSAN node will contain an SRM, while in one instance of time one node only (the master) will make a decision for all nodes participating in the DSAN.

A single scanning node needs to decide whether the LU band under consideration is empty or not, hence it takes a local decision. The quality of detection (QoD), in terms of detection probability P_d and False Acceptance Rate (FAR), may be improved by a collaborative scanning system. In such a system Frequency Occupancy Information (FOI) is gathered by all individually scanning DSAN nodes and disseminated to the nodes participating in DSAN using a special signalling channel for this purpose. The properties of this Common Control Channel (like its bandwidth, SNR, data rate, MAC protocol and delay), the independence of the measurements taken and the number of nodes involved in the scheme all determine the expected gains in detection quality over locally-made-only decisions, see [5], [4].

In case, when the DSAN knows radio properties of the LU signal to be detected, or where interaction between DSAN and the LU is allowed (by means of some form of 'spectrum etiquette') one can resort to feature establishment - one identifies well known (deterministic) signal features of the primary user's signal like carrier waveforms or pilot tones. As, for instance, in broadcast situations, the primary user *wants* to be heard, it is expected that especially in bad SNR conditions feature establishment may outperform energy detection [6]. However, this can only be done in a DSAN. In [7] it is argued that sub-noise detection is actually a necessity in (TV) broadcast situations.

Observe that in an OSA network (OSAN), *only* scanning is allowed, so feature-related knowledge is not available. An option for the spectral analysis system in both OSAN and DSAN is to use (FFT-based) energy detection (power detection). In this case the scanning system works on *any* signal.

Now three questions arise: how good is energy detection in terms of QoD, is sub-noise energy detection possible and what deteriorates such a system?

In [6, 7] these issues were studied; an important conclusion was that especially the effect of unknown noise-levels deteriorates the QoD. The contribution of this paper is that we identify system issues that are a consequence of unknown noise-level uncertainty.

First, in section 2, we describe the analysis approach by Urkowitz [8], however using a power-based SNR. We characterise the decision statistic for deterministic signals in terms of its probability density function (pdf). In section 3 the question how good energy detection is is answered. Moreover, using a slightly generalised version of the analysis by Sonnenschein [9], the effects of noise level uncertainty are studied. In section 4 the consequences of the analysis for a DSAN architecture are presented: one needs to add a *noise-level measurement* function to the system architecture, especially if sub-noise detection is required. Section 5 concludes the paper.

2 Energy Detection

The problem of detecting energy in deterministic signals was addressed by Urkowitz [8]. In this section we briefly follow his approach and introduce a power-based SNR (as opposed to the energy one used in [8]). Finally, we relate Urkowitz' result to the power-based statistic we want to use for the detection decision.

Consider the following signal model:

$$x(t) = \varepsilon\, s(t) + n(t) \text{ with } \varepsilon \in \{0, 1\} \tag{1}$$

in which $s(t)$ is an information-bearing signal (using at this moment an unspecified modulation), $n(t)$ is a white-noise process and ε determines whether there is or is not a modulated signal. Basically the system is needed to establish (estimate) ε.

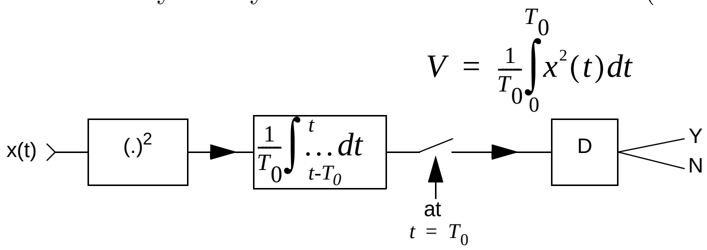


Figure 2: Urkowitz energy detection system. D is a decision device with threshold *th*.

Urkowitz's system is depicted in figure 2. His input signal $x(t)$ is either a low pass signal with bandwidth B or it is a bandpass signal with the same bandwidth. Moreover, he assumes that $s(t)$ is a deterministic signal, which is of course non information-bearing. We briefly iterate on this at the end of section 2.1.

First, it is assumed that $x(t)$ is a low pass signal (and the signals in (1) too). After observing $x(t)$ during the observation interval T_o, the system computes the decision statistic V (the approximation in (4) is used):

$$V \triangleq \frac{1}{T_o}\int_0^{T_o} x^2(t)dt \overset{(4)}{=} \frac{1}{2B\,T_o}\sum_{i=1}^{2B\,T_o} x^2(\frac{i}{2B}) \tag{2}$$

in which the right-hand side (rhs) of the second equality sign stems from the fact that $x(t)$ is a low pass signal with bandwidth B. With sample frequency $f_s = 2B$, sample time $T = 1/f_s$ we define the number of samples taken $N \triangleq 2BT_o$ and indeed, the observation interval $T_o = NT$ (again, the approximation in (4) is used):

$$V = \frac{1}{T_o}\int_0^{T_o} x^2(t)\,dt \overset{(4)}{=} \frac{1}{N}\sum_{i=1}^{N} x^2(iT). \tag{3}$$

The key observation is that for a signal $x(t)$, band-limited to B Hz,

$$x(t) \approx \sum_{i=1}^{2BT_o} x(i/2B)\,\mathrm{sinc}(2B\,t - i) \quad \text{for} \;\; 0 \le t \le T_o \tag{4}$$

holds, provided that T_o is long enough. For analysis purposes Urkowitz also introduces a second decision statistic V', related to V:

$$V' \triangleq \frac{T_o}{N_0/2}\,V \tag{5}$$

in which $N_0/2$ is the double-sided noise-power spectral density (PSD). It follows that

$$V' = \frac{1}{N_0/2}\int_0^{T_o} x^2(t)\,dt = \frac{1}{N_0/2}\,\frac{N\,T}{N}\sum_{i=1}^{N} x^2(iT) = \frac{1}{2B\,N_0/2}\sum_{i=1}^{N} x^2(iT) = \sum_{i=1}^{N} x'^2(iT) \tag{6}$$

in which $x'(iT) \triangleq x(iT)/\sigma_n$ is the noise-power normalised input-signal with noise power $\sigma_n^2 = B\,N_0$. Under hypothesis H_0 (so $\varepsilon = 0$) is $x'(iT)$ a Gaussian random variable (RV) with zero mean and variance 1. In that case is $x'^2(iT)$ a χ^2-RV, [10], with 1 degree of freedom (dof) and V', being the sum of N of these independent RVs, is χ^2-distributed with N dof.

Under hypothesis H_1 (so $\varepsilon = 1$) Urkowitz shows that

$$\begin{aligned} V &= \frac{1}{T_o}\int_0^{T_o} x^2(t)\,dt = \frac{1}{N}\sum_{i=1}^{N}(s(iT)+n(iT))^2 \text{ and} \\ V' &= \frac{1}{B\,N_0}\sum_{i=1}^{N}(s(iT)+n(iT))^2 = \sum_{i=1}^{N}(s'(iT)+n'(iT))^2 \end{aligned} \tag{7}$$

in which $x'(iT) \triangleq (s(iT)+n(iT))/\sigma_n = s'(iT)+n'(iT)$ is the noise-power normalised input-signal with noise power $\sigma_n^2 = B\,N_0$. In Urkowitz' analysis it is assumed that $s(t)$ is a deterministic signal, so that $x'(iT)$ is a Gaussian RV with mean $s'(iT)$ and variance 1. Then, under H_1, is V' a non-central χ^2-RV, [10], with N dof and parameter λ given by

$$\lambda \triangleq \sum_{i=1}^{N}(s(iT)/\sigma_n)^2 = \frac{E_s}{N_0/2} \text{ with } E_s = \int_0^{T_o} s^2(t)\,dt = T\sum_{i=1}^{N} s(iT)^2 \tag{8}$$

the *total* signal energy in the observation period.

So $\lambda = \frac{E_s/T}{\sigma_n^2} = \frac{E_s\,2B}{N_0\,B}$ and the second rhs of (8) follows. According to Urkowitz, λ is a signal-to-noise ratio (SNR), however, we will define SNR in another fashion. In terms of average signal power $P_s \triangleq E_s/T_o = E_s/(N\,T) \Rightarrow E_s = N\,T\,P_s$ we find

$$\lambda = \frac{E_s/T}{\sigma_n^2} = \frac{N\,T\,P_s/T}{\sigma_n^2} = N\,\frac{P_s}{\sigma_n^2} \triangleq N\,\mathsf{snr} \tag{9}$$

in which we presented our definition of SNR: $\mathsf{snr} = \frac{P_s}{\sigma_n^2}$, with average signal power $P_s = 1/T_o\int_0^{T_o} s^2(t)\,dt$ and noise power $\sigma_n^2 = N_0\,B$.

Now, let $x(t)$ be a bandpass signal with a bandwidth of B [Hz], centred around frequency f_0 [Hz] and angular frequency $\omega_0 = 2\pi f_0$. Its complex envelope is $\tilde{x}(t) = x_c(t) + j\,x_s(t)$ with $x_c(t)$ its in-phase component and $x_s(t)$ its quadrature component (following notation of [11]). With complex envelope $\tilde{x}(t) = \varepsilon\,\tilde{s}(t) + \tilde{n}(t)$, in-phase component $x_c(t) = \varepsilon\,s_c(t) + n_c(t)$ and quadrature component $x_s(t) = \varepsilon\,s_s(t) + n_s(t)$, the probability density functions of V' and V can be established. Urkowitz shows that these pdfs are identical to the ones found above (also (9) holds, $P_{\tilde{s}}/\sigma_{\tilde{n}}^2 = P_s/\sigma_n^2$).

2.1 Probability density functions of the decision statistics

For the expected value, variance and pdf of V' under H_0 we may write (formally), [10]:

$$\mu_{V'|H_0} = N,\ \sigma^2_{V'|H_0} = 2\,N \text{ and } f_{V'|H_0}(x) = f_{\chi^2}(x;N) \tag{10}$$

with dof N. In general, for two RVs for which $V = \alpha\,V'$ holds, it follows that $\mu_V = \alpha\,\mu_{V'}$, $\sigma^2_V = \alpha^2\,\sigma^2_{V'}$ and $f_V(x) = 1/\alpha\, f_{V'}(x/\alpha)$. So, we have with $\alpha = \sigma_n^2/N$ (see (5)) that

$$\mu_{V|H_0} = \sigma_n^2,\ \sigma^2_{V|H_0} = 2\,\sigma_n^4/N \text{ and } f_{V|H_0}(x) = N/\sigma_n^2\, f_{\chi^2}(N/\sigma_n^2\,x;N). \tag{11}$$

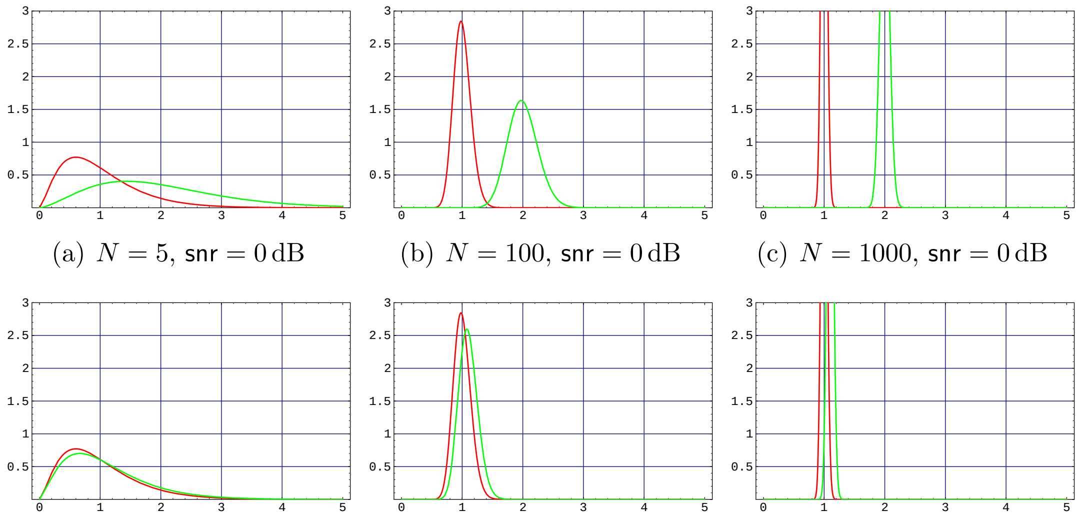
For the pdf of V' under H_1 we may write, [10]:

$$\begin{aligned}\mu_{V'|H_1} &= N+\lambda = N\,(1+\mathsf{snr}),\ \sigma^2_{V'|H_1} = 2\,(N+2\lambda) = 2N\,(1+2\,\mathsf{snr}) \text{ and}\\ f_{V'|H_1}(x) &= f_{nc\,\chi^2}(x;N,\lambda) = f_{nc\,\chi^2}(x;N,N\,\mathsf{snr})\end{aligned} \tag{12}$$

with dof N and parameter λ according to (9). We find

$$\begin{aligned}\mu_{V|H_1} &= \sigma_n^2\,(1+\mathsf{snr}),\ \sigma^2_{V|H_1} = 2\,\sigma_n^4\,(1+2\,\mathsf{snr})/N \text{ and}\\ f_{V|H_1}(x) &= N/\sigma_n^2\, f_{nc\,\chi^2}(N/\sigma_n^2\,x;N,N\,\mathsf{snr})\end{aligned} \tag{13}$$

To get a feel for the pdfs of V under both hypothesis, we plotted them for 'high' and 'low' SNR and for small and large N in figure 3. As can be seen by visual inspection of the graphs, for an $\mathsf{snr} = 0\,\text{dB}$ the two pdfs can be considered more or less separated for $N = 100$. For $\mathsf{snr} = -10\,\text{dB}$ even at $N = 1000$ the pdfs overlap too much to enable a sufficient QoD. However, one conjectures that by increasing N there is, in principle, no limit to the negative SNR at which one can obtain reliable signal detection. In the next section we show that noise-level uncertainty refutes this conjecture.



(a) $N = 5$, $\mathsf{snr} = 0\,\text{dB}$ (b) $N = 100$, $\mathsf{snr} = 0\,\text{dB}$ (c) $N = 1000$, $\mathsf{snr} = 0\,\text{dB}$

(d) $N = 5$, $\mathsf{snr} = -10\,\text{dB}$ (e) $N = 100$, $\mathsf{snr} =-10\,\text{dB}$ (f) $N = 1000$, $\mathsf{snr} =-10\,\text{dB}$

Figure 3: Pdf of decision statistic V under hypothesis H_0 and H_1 for different SNR's and number of samples N ($\sigma_n^2 = 1$).

In case of non-deterministic signals (e.g. a complex (possibly non-zero mean) white gaussian process $\tilde{s}(t)$) the analysis approach can be adapted with result that the pdf $f_{V|H_1}(x)$ of the decision statistic alters, however *not* its mean $\mu_{V|H_1}$. Moreover, the variance changes only slightly (especially in the case of low SNR): $\sigma^2_{V|H_1} \le 2\,\sigma_n^4\,(1+\mathsf{snr})^2/N$. Also, in case one is not really interested in large deviations from the mean, a gaussian approximation is good enough for the pdfs of V and V'.

3 Noise-level uncertainty

The QoD is determined by

$$FAR = \int_{th}^{\infty} f_{V|H_0}(x)\,dx = \int_{\alpha_F}^{\infty} \sigma_0\, f_{V|H_0}(\mu_0 + y\,\sigma_0)\,dx \triangleq Q_F(\alpha_F) \tag{14}$$

$$P_d = \int_{th}^{\infty} f_{V|H_1}(x)\,dx = \int_{-\alpha_D}^{\infty} \sigma_1\, f_{V|H_1}(\mu_1 + y\,\sigma_1)\,dx \triangleq Q_D(-\alpha_D) \tag{15}$$

in which the decision threshold th is assumed to be above μ_0 and below μ_1, see figure 3: $th = \mu_0 + \alpha_F\,\sigma_0 = \mu_1 - \alpha_D\,\sigma_1$ and $\alpha_F,\ \alpha_D > 0$. Moreover, the functions $Q_F(x)$ and $Q_D(x)$ which give the area under the tail of the pdfs are assumed to be invertible: $Q_F^{-1}(FAR) = \alpha_F$ and $Q_D^{-1}(P_d) = -\alpha_D$. In case both $f_{V|H_0}(x)$ and $f_{V|H_1}(x)$ are gaussian, one may write $Q_D(x) = Q_F(x) = 1/\sqrt{2\,\pi}\,\int_x^\infty \exp(-y^2/2)\,dy$, the area under the gaussian tail (as in [9]). For example, in the gaussian case a choice of $\alpha_D = \alpha_F = 3$ results in $FAR = 1 - P_d \approx 10^{-3}$; in case $\alpha_D = \alpha_F = 7$, $FAR = 1 - P_d \approx 10^{-12}$.

Now suppose we want a detection system with a required FAR and P_d, FAR_{req} and $P_{d,req}$ (so, the design parameters $\alpha_{D,req}$ and $\alpha_{F,req}$ are available). Then we find (following [9], with the remark that our presentation holds for general pdfs) by taking μ_0 and σ_0 from (11):

$$th = \mu_0 + Q_F^{-1}(FAR_{req})\,\sigma_0 = \sigma_n^2\,(1 + Q_F^{-1}(FAR_{req})\,\sqrt{2/N}) \triangleq \sigma'\,\sigma_n^2 \tag{16}$$

and, taking μ_1 and σ_1 from (13)[1],

$$P_{d,req} = Q_D(-\alpha_{D,req}) = Q_D\left(\frac{th - \mu_1}{\sigma_1}\right) = Q_D\left(\frac{Q_F^{-1}(FAR_{req})\,\sqrt{2/N} - \mathsf{snr}}{\sqrt{1 + 2\,\mathsf{snr}}\,\sqrt{2/N}}\right). \tag{17}$$

In our cognitive radio context we want to detect a LU signal above or below the noise level and specify this signal by its power $P_s = \mathsf{snr}\,\sigma_n^2$ at which QoD has to be achieved (in fact snr is a *required* SNR). So, unlike in [9], we want to solve (17) for N. By applying $Q_D^{-1}(.)$ to the left and right-hand sides of (17) we find

$$-\alpha_{D,req} = \frac{\alpha_{F,req}\,\sqrt{2/N} - \mathsf{snr}}{\sqrt{1 + 2\,\mathsf{snr}}\,\sqrt{2/N}}, \tag{18}$$

and finally

$$N = 2\,\frac{(\alpha_{D,req}\sqrt{1 + 2\,\mathsf{snr}} + \alpha_{F,req})^2}{\mathsf{snr}^2}. \tag{19}$$

As the detection system has to set a threshold $th = \sigma'\,\sigma_n^2$ (says (16)), it has to make an assumption about the noise level. Suppose one assumes $\widehat{\sigma_n^2}$, and from there selects the detection threshold $\widehat{th}$. Assume the *noise-level uncertainty* to be bounded: $(1-\epsilon_1)\sigma_n^2 \le \widehat{\sigma_n^2} \le (1+\epsilon_2)\,\sigma_n^2$ with $0 \le \epsilon_1 < 1$ and $\epsilon_2 \ge 0$. Then, to be on the safe side, one selects the threshold $\widehat{th} = U\,th$ with *peak-to-peak noise uncertainty* $U \triangleq \frac{1+\epsilon_2}{1-\epsilon_1} \ge 1$, [9]. With $th = \mu_0 + Q_F^{-1}(FAR_{req})\,\sigma_0$ we find:

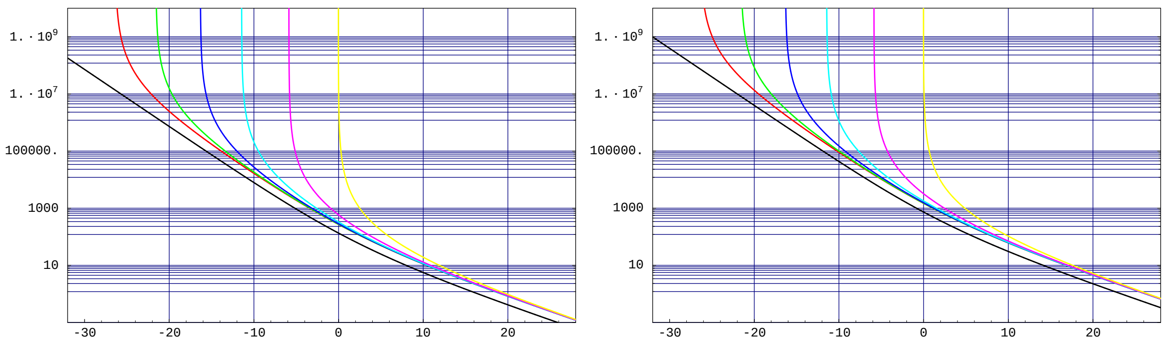
$$P_{d,req} = Q_D\left(\frac{U\,th - \mu_1}{\sigma_1}\right) = Q_D\left(\frac{(U-1) + U\,Q_F^{-1}(FAR_{req})\,\sqrt{2/N} - \mathsf{snr}}{\sqrt{1 + 2\,\mathsf{snr}}\,\sqrt{2/N}}\right). \tag{20}$$

[1]As was observed in section 2.1, the expression for σ_1 in the case of a (non-zero mean) white gaussian process $\tilde{s}(t)$ differs from the one used here and in [9]. Especially for low SNR the differences are irrelevant.

This can be re-written by applying $Q_D^{-1}(.)$ to the left and right-hand sides of (20):

$$N = 2\,\frac{(\alpha_{D,req}\sqrt{1+2\,\mathsf{snr}} + U\,\alpha_{F,req})^2}{(\mathsf{snr}-(U-1))^2}, \text{ for } \mathsf{snr} > U-1. \tag{21}$$

In which the condition stems from a step in the derivation, $\sqrt{\frac{2}{N}} = \frac{\mathsf{snr}-(U-1)}{\dots}$, which has only a solution if the rhs is positive. Observe that the condition $\mathsf{snr} > U-1$ poses a *hard limit* on the power $P_s = \mathsf{snr}\,\sigma_n^2$ at which a LU signal can be detected in the case of noise level uncertainty. In figure 4 we show for modest U ($1 \leq U \leq 2$ so $0\,\text{dB} \leq U_{dB} \leq 3\,\text{dB}$) the number of samples N that need to be taken in order to achieve a certain QoD (specified by $\alpha_{D,req}$ and $\alpha_{F,req}$) for a LU signal specified by $P_s = \mathsf{snr}\,\sigma_n^2 = \mathsf{snr}$ (so $\sigma_n^2 = 1$). Observe that going from $\alpha_{D,req} = \alpha_{F,req} = 3$ to $\alpha_{D,req} = \alpha_{F,req} = 7$ only increases the number of samples N by approximately a factor of 5, while the probabilities involved go from 10^{-3} to 10^{-12} (in case $Q_\bullet(x)$ is gaussian).



(a) $\alpha_{D,req} = \alpha_{F,req} = 3$. (b) $\alpha_{D,req} = \alpha_{F,req} = 7$.

Figure 4: Number of samples N (vertical) required for the detection of a LU signal with power $P_s = \mathsf{snr}\,\sigma_n^2 = \mathsf{snr}$ [dB] (horizontal) and noise uncertainty of (per curve from left to right) $U_{dB} = 0$, 0.01, 0.03, 0.1, 0.3, 1, 3 dB.

4 Noise-level measurements in a DSAN architecture

In the AAF DSAN [2,3] two types of network nodes are distinguished: vehicle nodes and personal nodes. In all of these nodes scanning may be performed. The scanning and baseband transmission takes place in a time division duplexing (TDD) fashion in order to overcome analog frontend saturation and to allow for collaborative scanning [3, 5]. What are the consequences of noise-level uncertainty for a DSAN architecture?

In order to answer this question the first issue to be decided upon is signal power P_s of the Licensed Users (LUs) that need to be detectable by the DSAN. In case $P_s > \sigma_n^2$, noise level uncertainty does not increase the number of samples N too much provided that $U_{dB} \leq 1\,\text{dB}$, as can seen from figure 4. If however sub-noise energy detection is necessary ($P_s < \sigma_n^2$) the noise level uncertainty may seriously hamper QoD: the limit of detectability is given by $\mathsf{snr} > U-1$. By inspection of figure 4 one may appreciate that at approximately 5 dB to the right of the limiting SNR the number of samples has not increased too much.

In the DSAN architecture noise-level uncertainty can be minimised at different levels. First in a node itself. A calibration mechanism can be added to the node in which the antenna is decoupled from the analog frontend and the signal from a temperature-stable noise source is input to the frontend. This enables to estimate the noise factor of the frontend and thereby the noise level. For this, a *calibration phase* has to be added in the TDD frame of the network. It has to be researched how often calibration needs to be done, how long it takes and what noise level uncertainties can be achieved.

As the provision of a well-known and stable noise source in a *personal node* may be too battery-power consuming, such a source may be provided in a *vehicle node* that has more energy available. In that case, information regarding the noise level measured at the vehicle node has to be transmitted to the personal nodes. For this a period of time has to be reserved in the TDD frame. The resulting noise-level uncertainty of a collaborating calibration system is to the authors knowledge an open issue.

5 Conclusions and future work

In this paper the performance of a simple energy detection system was studied: noise-level uncertainty poses a hard limit on the detectability of especially sub-noise signals.

Future work could consist of determining at what SNR's licensed user signals need to be detected. Subsequently the QoD in terms of $\alpha_{D,req}$ and $\alpha_{F,req}$ has to be established. Also practical values of U need to be found. Then, one can establish the necessity, place in the DSAN and cost of the noise-measurement functionality.

Finally, the the analogue front-end architecture and the position and dimensioning of an ADC for the DSAN spectral scanning system have to be designed.

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